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The impact of COVID-19 on mobility choices in Switzerland☆

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ABSTRACT

We study the effect of the COVID-19 pandemic and the associated government measures on individual mobility choices in Switzerland. Our data is based on over 1,600 people for which we observe all trips during eight weeks before the pandemic and until May 2021. We find an overall reduction of travel distances by 60 percent, followed by a gradual recovery during the subsequent re-opening of the economy. Whereas driving distances have almost completely recovered, public transport re-mains under-used. The introduction of a requirement to wear a mask in public transport had no measurable impact on ridership. The individual travel response to the pandemic varies along socio-economic dimensions such as education and house-hold size, with mobility tool ownership, and with personal values and lifestyles. We find no evidence for a significant substitution of leisure travel to compensate for the reduction in work-related travel.

1. Introduction

Switzerland was hit hard and early by the COVID-19 pandemic, shortly after Italy. By early April of 2020, it had among the highest infection rates per capita worldwide. Due to a series of government measures, the outbreak was contained relatively quickly, but the pandemic returned in a series of additional waves.

In this paper, we examine the effect of the pandemic, and of the introduction and removal of the governmental measures, on individual mobility in Switzerland. In January 2020, we had concluded a large-scale field experiment in which we had tracked the mobility behavior of more than 3,500 participants using a smartphone-based app. After the virus outbreak, we re-contacted all participants about continuing the study, and about half of them agreed to do so. We thus have highly disaggregated mobility data for a large sample for the time before and during the pandemic. Besides mobility choices, we have detailed information about the socio-demographic characteristics of the participants as well as a wide set of preference parameters derived from two surveys. The combination of detailed GPS tracks and individual information spanning the onset of the pandemic provides us with a rare opportunity to study the effect of the COVID-19-crisis and the associated public policy measures on individual mobility.

During what is termed the "soft" lockdown in Switzerland, we observe a reduction in the overall travel distance of around 60 percent relative to the time before the pandemic. This is remarkable, given that Switzerland never formally restricted public or private transport. People were encouraged to stay at home, but there was no actual travel/movement ban. In this sense, staying at home can be

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interpreted as contributing to the public good. The total distance traveled almost returned to its pre-pandemic level by July 2020, before decreasing once again to 60 percent of the baseline at the peak of the second wave. By May 2021, the end of our sample period, travel distance was at around 80 percent of its pre-pandemic level. This partial overall recovery masks a significant variation over the transport modes: Whereas driving distances are almost back to pre-COVID levels, the occupancy of public transport (PT) stagnated at around 40 percent relative to the time before the pandemic. The introduction of a formal requirement to wear a mask in PT ("mask requirement" hereafter) did not significantly alter people's propensity to use PT. If employees were to return to their work places before the trust in the safety of public transport is restored, the consequence could be a severe increase in road congestion. This is problematic from a public policy point of view, as both congestion and increasing road capacity are very costly. In addition, a persistent decrease in PT usage may force providers to reduce the scope and quality of service in the medium to long term, leading to even more cars on the road. This is especially problematic for Switzerland since the Swiss strategy in line with the Paris Agreement foresees zero emissions from land transport by 2050 (Swiss Federal Office for the Environment, 2021).

We observe a pronounced heterogeneity of the response to the pandemic and policy measures in our sample. In order to better understand this heterogeneity, we engage in a machine-learning exercise based on a causal forest to identify those variables among our rich survey information that best explain the individual-level response. In a second step, we include these variables as interaction terms in a more standard regression analysis. We find that the reduction in mobility during the pandemic was more pronounced among households with children and respondents with a tertiary education and a PT subscription. In contrast, full-time employment was a predictor for increased mobility, along with personal "values" and "lifestyles" that were elicited using a standardized methodology. Furthermore, we find no evidence that people increased their leisure travel to substitute for the reduction in work-related mobility.

A growing number of studies has examined the impacts of the initial lockdowns on transport behavior in various countries after the onset of the pandemic. This literature can be separated into two broad groups. The first group is based on surveys in which the participants were asked to describe how their transport (and sometimes other) behavior changed after March of 2020.[1] The second group is based on "revealed" transport choices, which is measured using GPS tracking, other forms of location-based mobile data, or ticket purchases.[2] Direct measurement has the advantage that it avoids the response and recall biases that routinely plague survey-based studies, but this often comes at the price of having little or no information about the involved people (other than their tracks). In our study, we combine GPS data coupled with in-depth surveys from before and after the pandemic, which provides us with a unique opportunity to investigate the heterogeneity of the person-level response.

In a closely related study[3] using the same tracking panel, Molloy et al. (2021) examine the effect of the pandemic on aggregate outcomes such as the number of trips per day, travel speed and activity spaces and the average reduction in total distance traveled. In the current paper, we further exploit the disaggregated nature of our data and examine the heterogeneity of the transport-related response to the pandemic on the person-level using a regression-based analysis. We include not only the standard socio-demographic characteristics, but also information about personal values and lifestyles that were collected in surveys before the start of the pandemic.

In the next section, we provide some background information and Section 3 presents the data. Section 4 presents our empirical framework, Section 5 the regression results, and Section 6 offers a discussion and some conclusions.

2. Background

2.1. The COVID-19 pandemic in Switzerland

The first confirmed case of COVID-19 was registered in Switzerland on February 25, 2020. The situation deteriorated quickly and by late March, new infections exceeded 1,000 per day. By the end of our sample period (May 30, 2021), over 684,000 confirmed cases and over 10,800 deaths have been registered.[4]

The Swiss Federal government declared an "extraordinary situation" on March 16, 2020 and thus assumed competencies normally in the hands of the cantons.[5] Under these temporary rules, most publicly accessible and non-essential businesses were closed, along with schools and recreational facilities. Most private businesses were not affected by the ruling, but employers were asked to make home office and flexible hour arrangements possible to avoid rush hour peaks in transport. Grocery stores, health care-related institutions, post offices, banks, transport services and governmental offices were exempt. The national borders were closed with the

[1] See, e.g., the studies covering Australia (Beck and Hensher, 2020a,b), Germany (Anke et al., 2021), Japan (Parady et al., 2020), the Netherlands (De Haas et al., 2020), Poland (Borkowski et al., 2021), Spain (Aloi et al., 2020), Sweden (Bohman et al., 2021), Turkey (Shakibaei et al., 2021) or the United States (Shamshiripour et al., 2020). For studies with a global coverage, see Barbieri et al. (2021); Dingil et al., 2021; Shibayama et al. (2021); Abdullah et al. (2020).

[2] See, e.g., studies covering Finland (Järv et al., 2021), China (Jia et al., 2020), Hong Kong (Chan et al., 2021), Japan (Yabe et al., 2020), New Zealand (Wen et al., 2022), Spain (Sanz et al., 2021), South Africa (Carlitz and Makhura, 2021), Sweden (Jenelius and Cebecauer, 2020). For multi-country analyses, see Da Silva et al., 2021; Franks et al., 2022; Lee et al. (2020); Xiong et al. (2020); Google (2022); Apple, 2022; Habib and Anik, 2021; Tirachini and Cats (2020).

[3] Molloy et al. (2020b) analyses the first month of the pandemic in Switzerland based on the same panel.

[4] To put this in perspective, the population in Switzerland is currently 8.57 million.

[5] All past and present measures imposed and lifted by the federal government and cantons can be found here: https://www.bag.admin.ch/bag/en/home/krankheiten/ausbrueche-epidemien-pandemien/aktuelle-ausbrueche-epidemien/novel-cov/massnahmen-des-bundes.html.

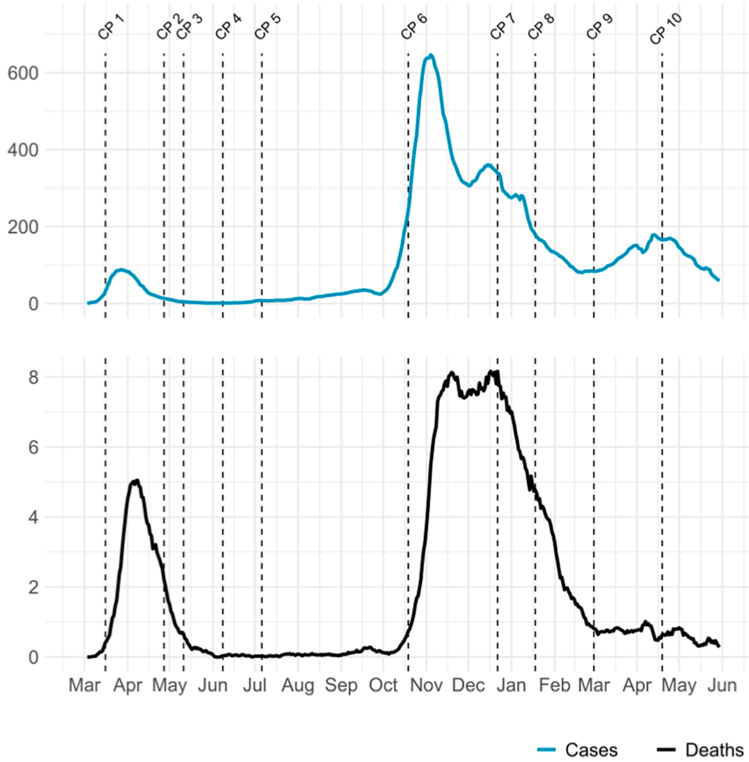

Fig. 1. COVID-19 Cases and Deaths (7 day incidence per 100,000 inhabitants). For a description of the Covid Periods (CPs), see main text. Source: https://www.corona-data.ch/.

exception of work-related travel and Swiss citizens returning from abroad.

The COVID-19-measures also targeted private individuals. Public gatherings of more than 5 were forbidden, and social distancing of 2m was mandated for every-one not living in the same household (this was later reduced to 1.5m). Although strict, the measures were less severe than in many other European countries, including Switzerland's neighbors. Importantly, people were allowed to leave their homes throughout the pandemic and most of the economy remained open. Thus, the Swiss measures were labeled as a "soft" lockdown, in comparison to more stringent measures elsewhere.[6] The first pandemic wave peaked at the beginning of April and then decreased.

Public transport service was maintained due to its high relevance for the Swiss economy. The federal government advised "individuals at risk" (i.e., those above 65 or with pre-existing health conditions believed to lead to more severe cases of COVID-19) not to travel or to use private transport if necessary.

The restrictions were gradually lifted as the infection rate decreased. On April 27, 2020, a first group of businesses were allowed to re-open (including garden centers, hair salons and, somewhat idiosyncratically, tattoo parlors) and hospitals were allowed to perform non-essential procedures again. On May 11, schools re-opened for grades 1–9 and most types of businesses resumed operation, including restaurants and bars.

On June 8, the restrictions were lifted for high schools and universities, as well as for all events of up to 300 individuals. All leisure and entertainment facilities re-opened, with a limit of 1,000 individuals for sports events. The national borders to the neighboring countries were re-opened on June 15. On June 19, the extended but temporary powers of the federal government officially expired. The social distancing mandate has remained in place (now enforced by the cantons).

Masks were initially not recommended, but eventually mandated for situations where social distancing could not be maintained (e.g. in doctors' offices or hair salons). On July 6, masks were mandated for use in public transport as well. In addition, some cantons imposed mask mandates for grocery stores and shops.

The infection and death rates remained stable over the summer months of 2020. However, in the fall the situation worsened again, resulting in the second wave of the pandemic for Switzerland. From October 19 the government mandated a ban on public gatherings of more than 15 people, that food and drink may only be consumed while sitting in restaurants and bars, and that masks must be worn inside at any publicly accessible location. These included public transport stations and stops, restaurants and bars, sports and cultural

[6] By "soft" lockdown we mean a situation in which travel was restricted by normative appeals, whereas a "hard" lockdown would restrict mobility by law. Although both types will reduce travel, the "soft" version relies on people's willingness to contribute to what is essentially a public good, whereas the latter does not.

facilities and venues, supermarkets and other shopping venues, and doctor's practices, among others. On November 2, universities had to switch to remote learning, whereas schools remained open.

During December the government implemented further measures. On December 9 there was a reduction in the capacity for shops, followed by a curfew of 19:00 for most shops, cultural venues, and sports facilities (except bars, restaurants, and takeaway shops). Gatherings of more than 5 persons were prohibited with the exception of religious festivals, burials, and political events. From December 22 all food service locations, cultural venues, and sports facilities were closed and shops' capacities were further reduced. In January 2021, the government extended the measures from December to the end of February 2021. From January 18 home office became mandatory and non-essential shops were closed.

From March 1 the government mandated a reopening of shops, cultural venues, and sports facilities, while gatherings of up to 15 persons were allowed outside. All other measures from December were extended until March 31. On April 19 restaurants and bars were allowed to reopen their outside seating areas and universities could return to in-person learning. During May the government presented a road map for further reopening measures dependent on the pandemic situation.

For our empirical analysis, we use this timeline to divide the pandemic into 10 distinct COVID periods (CPs):

CP 1: March 16–April 26, 2020 (first lockdown).
CP 2: April 27–May 10 (reopening of some businesses).
CP 3: May 11–June 7 (reopening of mand. school and most businesses)
CP 4: June 8–July 5 (reopening of all schools and recreational facilities)
CP 5: July 6–October 18 (mask obligation in public transport).
CP 6: October 19–December 21 (Rule of 15 people, mask mandate, remote learning).
CP 7: December 22–January 17 (second lockdown).
CP 8: January 18–February 28 (Lockdown extended, home office mandatory).
CP 9: March 1–April 18 (reopening of shops, sports facilities and cultural venues).
CP 10: April 19–May 30 (reopening of restaurants and bars).

Fig. 1 shows weekly new infections and COVID-19-related deaths per 100,000 inhabitants until the end of May 2021.

The first vaccines became available in January 2021. Due to the initial scarcity of vaccination doses and the priority given to the most vulnerable persons, the majority of the Swiss population aged 18–65 was vaccinated only after the end of our sample period. Towards the end of 2021, the Omicron wave hit Switzerland (like most other countries), but this third wave is excluded from the current analysis. On April 1, 2022, all federal measures related to the pandemic were dropped.

2.2. The MOBIS and MobisCovid panels

The MOBIS study is a large-scale field experiment that took place in Switzerland between September 2019 and January 2020 (Hintermann et al., 2021). During this study, the individual mobility behavior of the participants was recorded using a smartphone-based tracking app.

A sample of 91,000 people living in urban agglomerations in both the German- and French-speaking parts of Switzerland was invited to participate in the study by letter. Recipients were asked to complete an online survey designed to collect socio-demographic information, mobility patterns and preferences about transport policies. Respondents were filtered based on certain inclusion criteria, most importantly using a car on at least two days a week and not working as a professional driver. Those that qualified were invited to participate in a tracking-based study.

Around 22,000 people completed the introductory survey and 5,466 of which registered to participate in the tracking study. Tracking took place by means of the Catch-My-Day GPS-tracking app developed by motion-tag, Berlin. The app records all outdoor movements, groups the GPS points into stages, trips and activities, and imputes travel modes. Although the respondents were encouraged to verify the imputation and add a trip purpose, this was not required of them. For more details about the tracking app and response rates, see (Molloy et al., 2020a).

3,520 participants completed the final survey after the tracking period. Some of them continued using the tracking app despite the study's end, with roughly 400 participants still tracking by mid-March 2020. The remaining participants were invited to reactivate the tracking app. Over 1,200 re-installed the app and most resumed tracking. Along with those that never switched off the app, these participants make up the MobisCovid panel. Since the beginning of April, bi-weekly reports have been produced,[7] providing detailed information on mobility patterns during the various phases of restrictions compared to the baseline MOBIS period. The original MobisCovid panel has suffered from attrition, which is mitigated by the addition of participants from LINK[8] in the fall of 2020, with over 700 individuals having delivered tracking information up to the end of May 2021. The panel has further been augmented with a series of online surveys where respondents were asked about current working and living arrangements and asked to assess their own and others' risk of contracting a severe case of COVID-19. The MobisCovid panel used in this analysis is restricted to those individuals who continued tracking from the original MOBIS study and has over 365,000 person-day observations from 1,649 participants.

[7] Updates of the reports are available in English, German, and French at https://ivtmobis.ethz.ch/mobis/covid19/en/.
[8] https://www.link.ch/en/products/the-link-internet-panel/.

Table 1
MobisCovid and Microcensus (2015) Sample Comparison.

Variable	Value	Share (%)	
		MobisCovid	Microcensus
Access to car	Yes	90.5	67.8
	Sometimes	8.6	23.6
	No	0.8	8.5
Age	[18, 25]	12.6	13.6
	(25, 35]	13.8	21.4
	(35, 45]	23.5	23.0
	(45, 55]	26.1	23.3
	(55, 66]	24.0	18.7
Education	Mandatory	5.8	13.5
	Secondary	46.3	45.2
	Higher	47.9	41.4
Employment	Employed	73.0	67.9
	Self-employed	6.8	9.0
	Apprentice	0.6	2.1
	Unemployed	3.7	4.0
	Student	5.1	3.2
	Retired	4.1	4.6
	Other	6.7	9.2
Gender	Female	50.6	50.3
	Male	49.4	49.7
Household size	1	12.4	18.4
	2	33.3	32.1
	3	20.4	20.3
	4	25.7	20.6
	5 or more	8.2	8.6
Income	4,000 CHF or less	5.6	8.4
	4,001–8,000 CHF	28.9	30.1
	8,001–12,000 CHF	30.0	24.7
	12,001–16,000 CHF	16.3	12.0
	More than 16,000 CHF	10.5	9.4
	Prefer not to say	8.7	6.0
	Don't know		9.5
Language	German	69.0	67.1
	French	22.8	29.9
	English	8.2	3.0
Nationality	Switzerland	81.9	68.3
	Other	18.1	31.7

Notes: Sample descriptive statistics shown for MobisCovid (n = 1,649) and Swiss Microcensus 2015 (n = 13,196) samples. Swiss Microcensus sample restricted to age groups and home locations present in the MobisCovid sample.

3. Data

Table 1 shows the composition of the MobisCovid sample in comparison to the Swiss transport Microcensus (Swiss Federal Office of Statistics and Swiss Federal Office of Spatial Development, 2017), which is a representative survey about travel behavior that takes place every 5 years. We restrict the Microcensus sample to individuals aged 18 to 66 residing in a postcode that occurs in the MobisCovid sample to ensure a more "like-for-like" comparison. The MobisCovid sample is broadly similar to the Microcensus with some differences: our sample is more educated, has much higher car access, fewer individuals between 25 and 35 and more between 55 and 66 years old, a higher employment rate, fewer single and more four-person households, higher household income, fewer French speakers, and more Swiss nationals. These differences can be explained by self-selection and the focus of the MOBIS study on working-age people that drive at least two days a week and live in urban agglomerations in the German- and French-speaking regions of Switzerland.

Because weather information is an important predictor for some modes, especially in the leisure context, we complement our tracking data with data about temperature, precipitation and sunshine hours from MeteoSwiss[9] provided on a 1km × 1km grid resolution.

To allow for a nonlinear effect of temperature on travel choices, we define periods of heat and cold (in terms of degree days) for a trip j on day t as follows:

$$Heat_{jt} \equiv \max\{tmaxd_{jt} - 25,\ 0\} \tag{1}$$

[9] See https://www.meteoswiss.admin.ch.

Table 2
Descriptive statistics for selected variables.

Variable	Mode	Phases		
		All	Baseline	COVID
Infections (weekly per 100k)	Total			108.51
				(153.78)
Distance (km)	Total	38.75	47.09	35.61
		(54.74)	(59.58)	(52.45)
	Car	29.75	33.88	28.19
		(47.21)	(49.28)	(46.31)
	PT	5.50	10.08	3.78
		(27.60)	(35.97)	(23.46)
	Bicycle	1.10	0.71	1.24
		(5.93)	(4.23)	(6.45)
	Walking	1.96	2.02	1.94
		(3.38)	(3.63)	(3.28)
Duration (min)	Total	81.60	92.28	77.58
		(83.80)	(96.24)	(78.22)
	Car	41.72	47.75	39.44
		(53.01)	(56.44)	(51.48)
	PT	8.35	16.40	5.31
		(35.16)	(54.51)	(23.42)
	Bicycle	3.80	2.31	4.36
		(18.39)	(13.14)	(19.99)
	Walking	26.92	25.24	27.56
		(49.69)	(55.71)	(47.20)
Trips	Total	4.04	4.41	3.90
		(2.94)	(2.86)	(2.96)
Cold	Total	5.29	6.30	4.92
		(4.78)	(4.47)	(4.83)
Heat	Total	0.28	0.03	0.38
		(1.10)	(0.26)	(1.27)
Sunshine (hours)	Total	5.78	3.68	6.57
		(4.91)	(3.50)	(5.12)
Precipitation (mm)	Total	2.67	2.80	2.63
		(5.49)	(4.93)	(5.68)

Notes: Values calculated as daily means for the full sample ("All", n = 368,886), the baseline period from 02.09.2019 to 29.02.2020 ("Baseline", n = 100,994), and the COVID period from 01.03.2020 to 30.05.2021 ("COVID", n = 267,892). Standard deviations in parentheses.

$$Cold_{jt} \quad \equiv \quad \max\ \{10 - tmind_{jt},\ 0\} \tag{2}$$

The variables $tmaxd_{jt}$ and $tmind_{jt}$ refer to the daily maximum and minimum temperature, respectively, recorded in degrees Celsius at the grid point closest to the departure location for trip j.[10] In addition, we include precipitation and the number of sunshine hours, recorded on the same grid. To compute the corresponding values per person and day, we take the average of the heat, cold, precipitation and sunshine values across all trips taken by person i on day t.

Table 2 shows average daily distances, duration, and trip counts for our sample, along with information about the weather and infection rates. The values are given for the whole period (September 2019 through May 2021), as well as for the "Baseline" (September 2019 through February 2020) and "COVID" (March 2020 through May 2021) periods. Descriptive statistics for additional variables entering the causal forest and regression analyses described below are presented in Table A.1.

4. Empirical framework

We estimate the proportional change of outcome variable Y_{it} for person i on day t as a function of a set of explanatory variables. To obtain the average effect of the COVID-19-subperiods on mobility choices, we start with the following regression:

$$\ln(Y_{it}) = c + \alpha \cdot CW_t + \beta \cdot \ln(W_{it}) \times [\mathbf{1}\ WE_t] + \gamma \cdot X_{it} + \delta \cdot D_t + \mu_i + u_{it} \tag{3}$$

The vector CW_t contains a series of "COVID Week" dummies. The first dummy, which we refer to as "Week 0", is equal to one during the week starting on March 9, 2020; the second dummy marks the week starting on March 16, and so on. The sample ends on May 30, which is the last day of COVID Week 63. In addition to these CW dummies, we include additional dummies for the first week of March and for weekends and holidays in the vector D_t. The baseline (=omitted) time period thus consists of work days from September 2019 through February 2020, which is captured by the constant c and the person FE. The estimated vector of coefficients $\hat{\alpha}$ measures the

[10] The grid is based on the Swiss CH1903 coordinate system, which necessitates a conversion from the standard GPS coordinates obtained from the tracking data to the Swiss coordinate system.

proportional change in Y_{it} during each week of the pandemic, relative to the person-specific baseline and corrected for weather.

The vector W_{it} contains weather information associated with the trips that are included in Y_{it}. This allows for an interpretation of the other coefficients at the average weather a person was exposed to during our observation period. Because the effect of weather on mobility could differ between work days and weekends, we enter the weather information by itself (the unit vector in the first position in the brackets) and interacted with the weekend-dummy WE_t. In some regressions, we also include additional variables in the vector X_{it}, in particular the infection rate.

We include person fixed effects (μ_i) to absorb unobserved heterogeneity that is constant across time. The error term u_{it} has an expectation of zero, but we allow for correlations within individuals and within calendar days by imposing two-way clustering.

Rather than estimating (3) in a log-linearized form, we exponentiate the equation and estimate it using a Poisson pseudo-maximum likelihood (PPML) model.[11] The PPML estimator only requires that the conditional mean is correctly specified and no additional assumptions need to be made about the distribution of the error term (Correia et al., 2020; Gourieroux et al., 1984). Furthermore, estimating the model with PPML solves the problem with zeroes and also addresses a potential bias that can arise in the presence of heteroskedasticity; see Santos Silva and Tenreyro (2006) for a discussion.[12]

The problem associated with having no control group (i.e., the impact of dynamic unobserved factors that drive the dependent variable independently of COVID) is arguably mitigated in the current context. The pandemic and the lockdown measures were extremely salient, such that we expect all other unobserved determinants of mobility to be of second-order importance. This is true especially in the beginning of our sample period. In contrast, mobility during the second lockdown was probably affected also by the Christmas period.

The approach outlined above allows us to estimate the average proportional change in the dependent variable during the pandemic. However, the overall effect is only part of the story, as we observe a pronounced heterogeneity in the response to the pandemic and the governmental measures. Understanding the drivers of this observed heterogeneity will be useful for policy makers in anticipating the distributional consequences of future policy measures for subgroups of the population.

Including all possible explanatory variables in a joint regression could lead to spurious results due to multi-collinearity. To pre-select the variables that predict the heterogeneity best among the large set from the various surveys, we therefore make use of a machine learning algorithm. The causal forest (CF) algorithm proposed by Wager and Athey (2018) is an ensemble method based on the random forest (RF) algorithm proposed by Breiman (2001).[13] Once a CF is trained, a test for calibration and potential heterogeneity in the estimated treatment effect can be applied using the approach of Chernozhukov et al. (2018). The variables that drive the potential heterogeneity are those where the most splits occurred while training the CF and provide a measure of "variable importance".

Consistent with our regression framework, we use September 2019 to February 2020 as the control period and the entire COVID period as well as CP1 (first lockdown) and CP7 and CP8 (second lockdown) as the treatment periods. As we are comparing COVID-19-subperiods to a baseline period without a contemporaneous control group, we cannot claim to identify causal effects of the measures on mobility behavior. Nonetheless, by controlling for a large set of covariates, the estimates from the CF and the resulting indicator of variable importance can inform the specification of regression models to uncover potentially heterogeneous responses to the COVID-19 measures.

Using the information from the CF, we specify the following regression.

$$\ln(Y_{it}) = c + \alpha \cdot CP_t + \beta \cdot CP_t \times Z_i + \mu_i + \mu_t + u_{it} \tag{4}$$

Here, CP_t is a vector of 10 COVID period dummies, and Z_i contains the person-specific variables identified by the CF algorithm to be relevant drivers of the observed heterogeneity. This includes information about socio-demographics, mobility tool ownership, personal values and lifestyles.

To elicit personal values, we used the scale originally developed by Schwartz (1992) and adapted by De Groot and Steg (2010) and Steg et al. (2014). The respondents were asked to what extent they consider the 16 value items as *guiding principles in their lives* (Schwartz, 1992). Responses were recorded on a Likert scale and aggregated to 4 meta-values particularly relevant for explaining environmentally relevant behavior: egoistic, altruistic, hedonic and biospheric.[14]

To capture respondents' "lifestyles" we applied the typology developed by Otte (2008), who defines two lifestyle-defining

[11] We use Stata's ppmlhdfe command developed by Correia et al. (2019) and Correia et al. (2020).

[12] Briefly, the expected value of the logarithm of a random variable depends both on its mean and its variance. If the variance of $e^{u_{it}}$ depends on the regressors, which is quite plausible given that no negative values for y_{it} are allowed, then u_{it} will depend on the log of these regressors too, which may lead to a bias.

[13] A CF is trained in the standard way by growing trees from random samples of the data to estimate an expected outcome (here, the change in the average distance traveled after vs before the onset of the pandemic). The final estimate is a weighted average of the estimates for each leaf in the tree. A key difference in the CF algorithm compared to other RF algorithms is how the quality of the splits at each node in a tree is determined. With the ultimate aim of explaining potential treatment effect heterogeneity, the splits at each node are made such that the difference in treatment effects across all "child" nodes in the tree is maximized.

[14] These values are based on the following items: Egoistic: social power (control over others, dominance), wealth (material possessions, money), authority (the right to lead or command), influential (having an impact on people and events) and ambitious (hard-working, aspiring). Altruistic: equality (equal opportunity for all), a world at peace (free of war and conflict), social justice (correcting justice, care for the weak) and helpful (working for the welfare of others). Hedonic: pleasure (joy, gratification of desires), enjoying life (enjoying food, sex, leisure etc.) and self-indulgent (doing pleasant things). Biospheric: respecting the earth (harmony with other species), unity with nature (fitting into nature), protecting the environment (preserving nature) and preventing pollution (protecting natural resources).

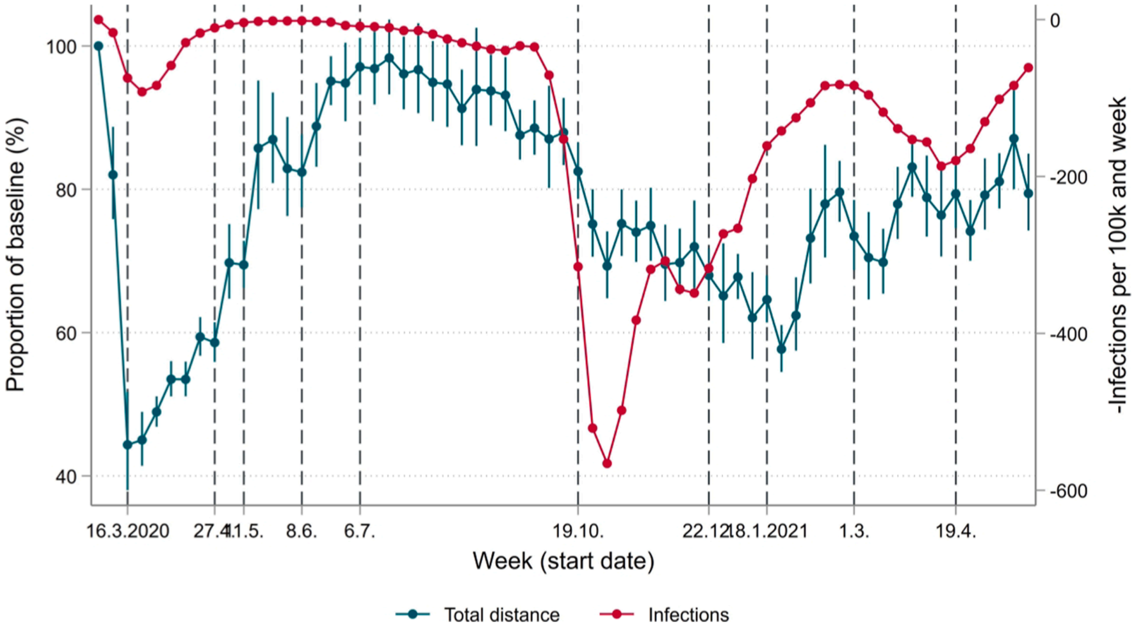

Fig. 2. Change in total distance travelled. This figure shows the estimated coefficients α in eq. (3) (left axis, with 90% confidence intervals), along with the infection rates (right axis). The vertical dashed lines mark the COVID periods defined in Section 2.1. The sample period ends on May 30, 2021.

dimensions: (1) modernity and biographical perspective[15] and (2) endowment level (including both material and cultural wealth).[16] The two dimensions are constructed based on the sub-items measured on a 4-point scale and then trichotomized taking the values 2 and 3 as the threshold values and defining the levels of modernity and biographical perspective as traditional (dimension index 1–2), semi-modern (dimension level 2–3) and modern (dimension level 3–4) and the levels of endowment as low (dimension index 1–2), middle (dimension index 2–3) and high (dimension index 3–4). The Otte lifestyle types result from the 9 possible pairs of dimension levels: (1) traditional workers (traditional, low endowment), (2) home-centered (semi-modern, low endowment), (3) entertainment-oriented (modern, low endowment), (4) conventionalists (traditional, middle endowment), (5) advancement-oriented (semi-modern, middle endowment), (6) hedonists (modern, middle endowment), (7) conservatives (traditional, high endowment), (8) liberals (semi-modern, high endowment) and (9) reflexives (modern, high endowment). Summary statistics of values and lifestyles are given in Table A.1.

5. Results

5.1. Effect on overall distance traveled

Fig. 2 plots the coefficients of the COVID Week dummies from using total travel distance as the dependent variable in (3).[17] The corresponding coefficient estimates are shown in the second column of Table A.2 in the appendix. The vertical dashed lines in the figure mark the start of the COVID phases defined in Section 2.1. The red line without confidence intervals plots the negative weekly infection rates.

The first lockdown was associated with a reduction in the total distance traveled by around 60% relative to the baseline period. By summer 2020, mobility had recovered to pre-COVID-19-levels, and in some weeks even exceeded the baseline. It decreased again with the onset of the second and wave and did not fully recover by the very end of the sample period. Note that the mobility response to the second wave was significantly smaller, despite the higher infection rates.

The overall response of travel to the pandemic can be separated into an intensive margin (i.e., the change in travel distance, conditional on person i traveling on day t) and an extensive margin (the change in the probability of person i to travel on day t). The latter is computed using a logit model. Columns 2–3 in Table A.2 indicate that initially, both margins of travel were reduced relative to the baseline: The proportional effects from the PPML model are less than unity and the marginal effects from the logit model are

[15] This dimension is measured based on the following 4 survey items: (i) I enjoy my life to the fullest degree, ii) I live according to religious principles, (iii) I hold onto my family's old traditions and (iv) I go out often.

[16] This dimension is measured based on the following 5 items: (i) I cultivate an upscale standard of life, (ii) Restaurant expenditures, (iii) Visiting art exhibitions and galleries, (iv) Reading books and (v) Reading nationwide newspapers.

[17] The results in this figure are based on regressions that include the weather controls (see column 1 of Table A.2). The results without the weather are qualitatively similar.

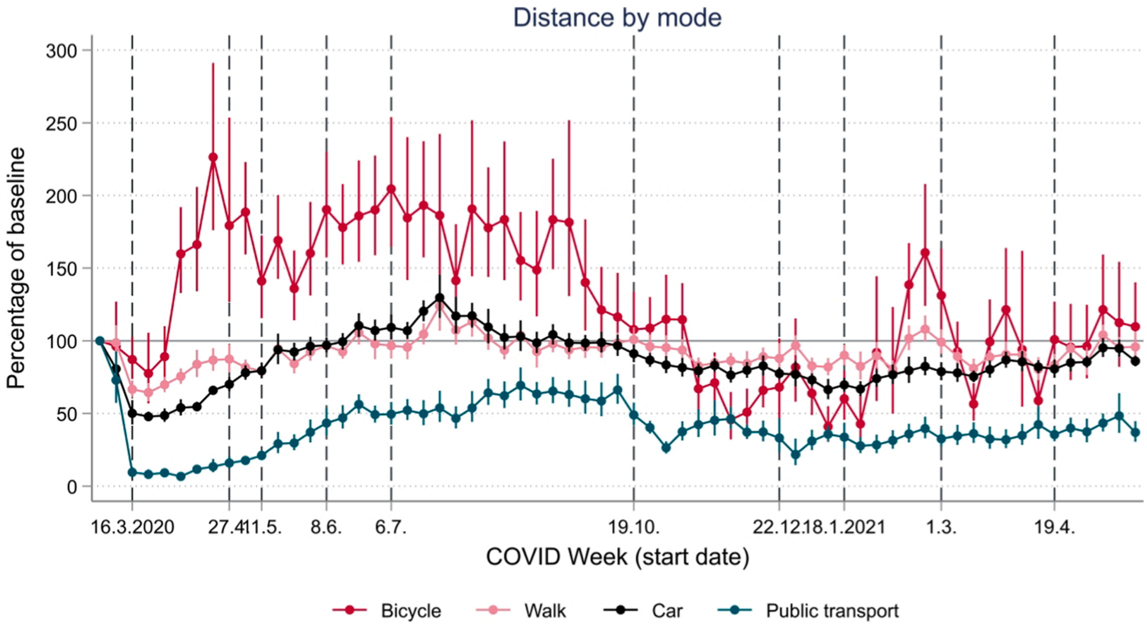

Fig. 3. Change in distance travelled by mode. This figure shows the estimated coefficients α in eq. (3) presented in the "Overall" columns for each mode in Table A.3, with distance by mode as the dependent variable. The vertical bars mark 90%-confidence intervals. The vertical dashed lines mark the COVID periods defined in Section 2.1. The sample ends on May 30, 2021.

negative. In the summer of 2020, the intensive margin became briefly positive (i.e., the people that left their home on a given day traveled longer distances) while the probability of travel has decreased throughout the pandemic. With the onset of the second wave in October of 2020, the intensive margin switched back to negative, such that by the end of the sample period, both margins of travel remained depressed relative to the baseline.

5.2. *Effect by mode*

Fig. 3 displays the change in distance by mode in response to the different waves of the pandemic. These results are derived by using distance by mode as the dependent variable in (3). The corresponding regression estimates are presented in Table A.3. The reduction in travel distance was particularly pronounced for public transport, which plunged to below 10% of the baseline at the beginning of the lockdown period and remains at much lower levels than before the pandemic even at the end of the sample period. Car and walking distances decreased too, but recovered very quickly and, during the summer of 2020, even exceeded pre-baseline levels. Last, we observe a remarkable increase in bicycle distances during the first wave, but not during the second. Note that even though we control for the weather in our regressions, the fact that our pre-pandemic information starts only in September 2019 makes this control imperfect, such that some of the increase in cycling in the Spring of 2020 may be a consequence of the sunny weather.

Interestingly, there is no visible uptick in public transport ridership once the mask requirement was introduced on July 6, 2020, which corresponds to the first day of COVID Week 17. This visual impression is confirmed by a series of statistical tests: The coefficient on COVID Week 16 in the PT-regression (i.e., the last week before the mask requirement) is not statistically different from those on COVID Weeks 17–19.[18] Since the PT mask requirement was the only COVID-19-related measure that changed on this date, we interpret this as an indication that any negative and positive effects of the mask requirements on PT ridership cancelled out each other.

Drivers responded to the lockdown both on the intensive and the extensive margins. Starting in week 10, however, the intensive margin becomes insignificant and then switches the sign: Conditional on driving on a given day, the panel participants drove *longer* distances in the summer of 2020 than during the baseline. In contrast, the propensity to drive has been affected negatively throughout. Therefore, the (more than complete) recovery of overall car travel after the first wave can be explained by fewer people driving longer distances, which suggests that some medium- and long-distance train trips were replaced by car trips. This may have been a "catch-up" phenomenon after the first lockdown, as in the second wave, both margins of travel remained consistently reduced.

For public transport, the reduction took place along both the intensive and the extensive margins. Although PT travel recovered somewhat from its first-wave drop, it remains significantly depressed throughout the sample period.

Bicycling significantly increased during much of 2020, along both margins. However, the level of cycling decreased towards winter and dropped below the baseline. No clear picture emerges for walking, as this can be a stand-alone mode (people walking to work) or serve as a first step for PT.

[18] The lowest p-value from this series of tests is 0.66, such that the null hypothesis of equal coefficients cannot be rejected by a long shot.

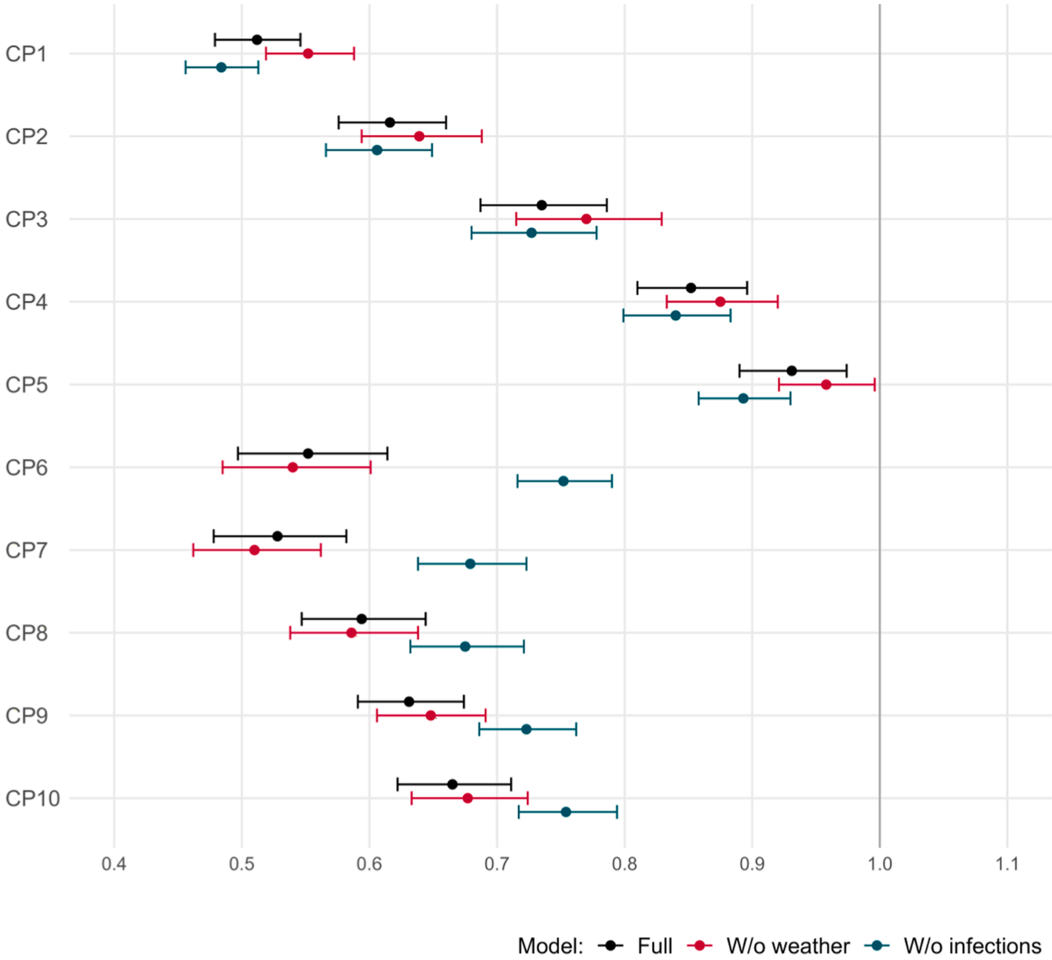

Fig. 4. Relative relevance of government measures and infection rates. *Notes*: This figure shows the estimated coefficients and 95%-confidence intervals on the COVID period dummies (CP1–CP10) for models (1)–(3) in Table A.4.

5.3. *Determinants of behavioral change*

The COVID week dummies capture the joint effect of the government measures, personal choices in the presence of high infection rates and seasonal variation. To disentangle these three sources of behavioral change, we estimate a model in which we replace the (many) COVID week dummies in (3) with the ten COVID period dummies defined above and, additionally, include infection rates in the regression. In order to allow for nonlinear and differential effects across waves, as suggested by Fig. 2, we include square terms and interactions with a wave-2-dummy. Due to the inclusion of the CP dummies, the infection variables capture the effect of change in the infection rates on travel *within* a COVID period. To allow for a differential response to the pandemic on weekdays and weekends, we also interact the CP dummies with the weekend dummy.

The reduction in distance traveled on workdays, by COVID period, are shown in Fig. 4 for three different models. The topmost point estimate (plus confidence intervals) in each COVID period shows the estimate for the respective CP dummy from the full model. The second estimate comes from a model in which the weather controls have been removed, and the third model consists of the full model minus the infection rates.

The figure implies that controlling for the weather is important only for isolated periods, but that overall the estimated reduction by CP with and without the weather controls is quite similar. The same is true for the infection rates during the first wave (CP1–CP5). Starting with wave 2, however, the infection rates explain a large share of the variation, such that dropping them from the model leads to very different point estimates relative to the full model. This indicates that in the beginning of the pandemic, most of the change in mobility behavior is captured by the governmental measures, whereas infection rates play an increasing role for individual travel choices as the pandemic progresses.

Last, we can use the coefficient estimates associated with the weekend dummies to learn about a potential substitution of travel between work and weekends. Fig. 5 shows the difference of weekend travel during the pandemic vs the baseline (this is the sum of the coefficients on the CP dummies and on the interaction terms with the weekend dummy in Table A.4). We find that the pandemic also

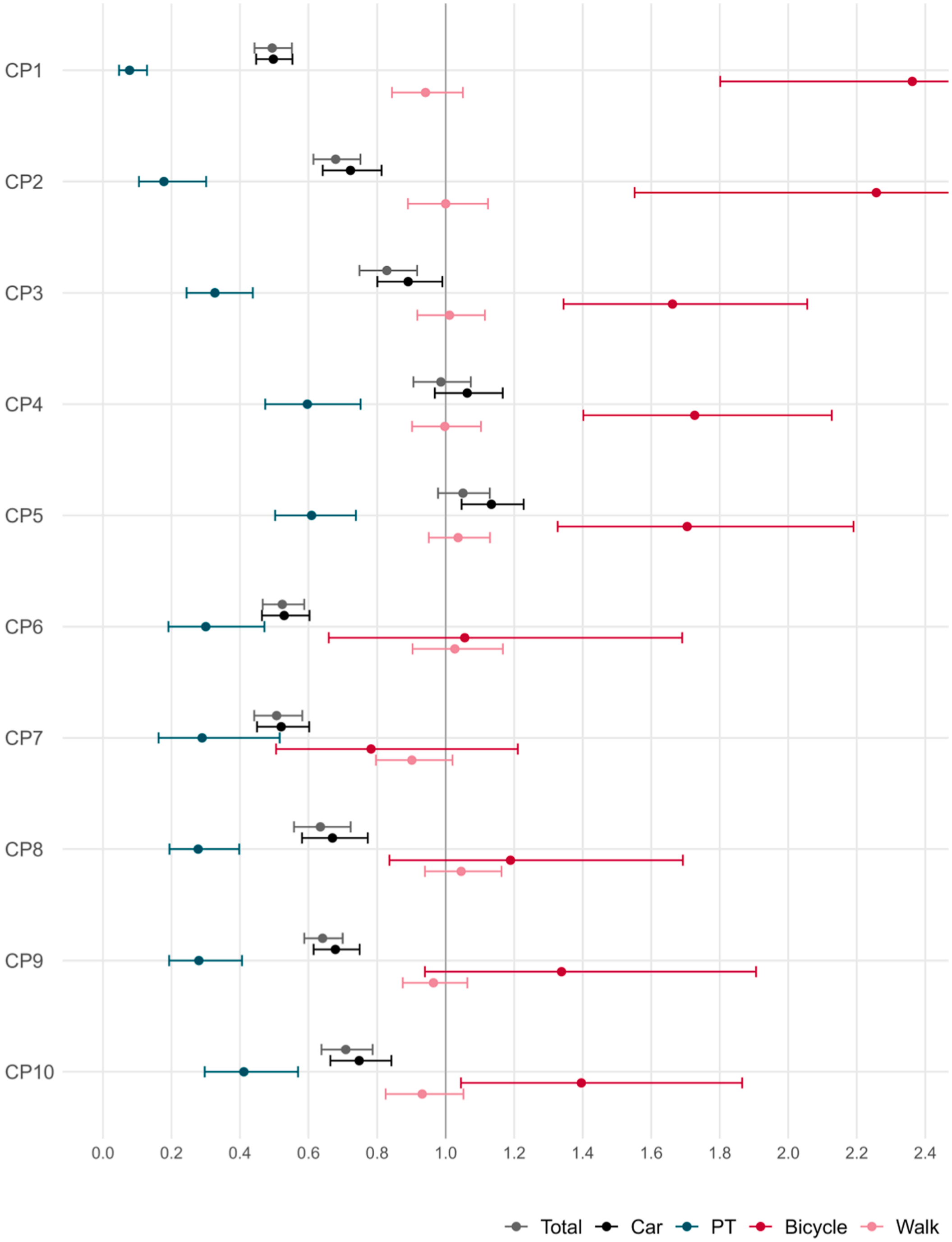

Fig. 5. Travel response to the pandemic during weekends. *Notes*: This figure shows the effect on weekend travel and 95%-confidence intervals for the COVID period dummies (CP1 to CP10) compared to the baseline period for models (1) and (4)–(7) in Table A.4.

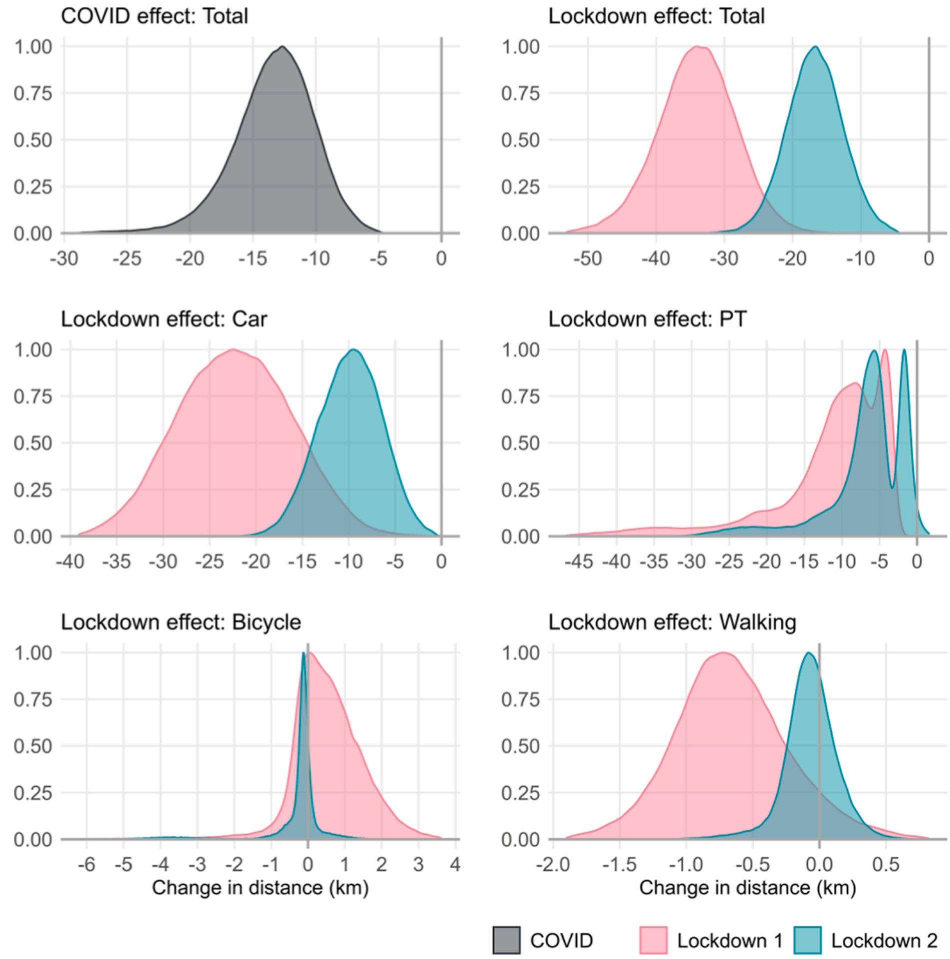

Fig. 6. Distribution of Change in Distance Traveled (km/day). *Notes*: This figure shows the heterogeneity of the response in travel distance to the pandemic over the entire sample period and during Lockdown 1 (CP1, 16.03.2020–26.04.2020 and Lockdown 2 (CP7 and CP8, 22.12.2020–28.02.2021) by mode (remaining panels) relative to the baseline period (02.09.2019–29.02.2020). The effect is computed using the CF algorithm by Wager and Athey (2018) and implemented in the R package "grf" (R Core Team, 2020; Tibshirani et al., 2020).

led to a reduction of overall weekend travel (besides travel on workdays, as shown in Tables A.2–A.4), with the exception of CP4 and CP5 for which the difference is not statistically significant. When looking at the change by mode on weekends, we once again see the bicycle boom. Weekend car travel was temporarily increased in CP5, suggesting some pent-up demand for driving that was released during this intermediate period of relative normalcy. However, considering the entire pandemic, there is no evidence for a systematic increase in weekend travel to compensate for the reduction in work-related mobility.

5.4. *Effect heterogeneity*

Fig. 6 shows the distribution in the change of total distances and distance by mode for the entire COVID-19 period and separately for the two lockdowns, using the CF algorithm.

The top left panel shows the significant reduction of travel distances during the COVID period as a whole. There is a wide range of heterogeneity both within and across modes for lockdowns 1 and 2, as shown by the two distributions in the top right panel.

Fig. A.1 in the appendix contains the variables from the CF analysis for the entire COVID period with a "better than random" information contribution to the model.[19] We combine the covariates identified by the CF in the vector Z_i and include them as interaction terms in eq. (4), separately for each of the ten COVID period dummies CP_t. The included variables can be grouped into socio-

[19] We generate a natural cutoff for the information contribution of each variable by adding two random variables. The continuous and dichotomous random variables capture random variation and, as such, all variables with a lower variable importance ranking represent nothing more than white noise.

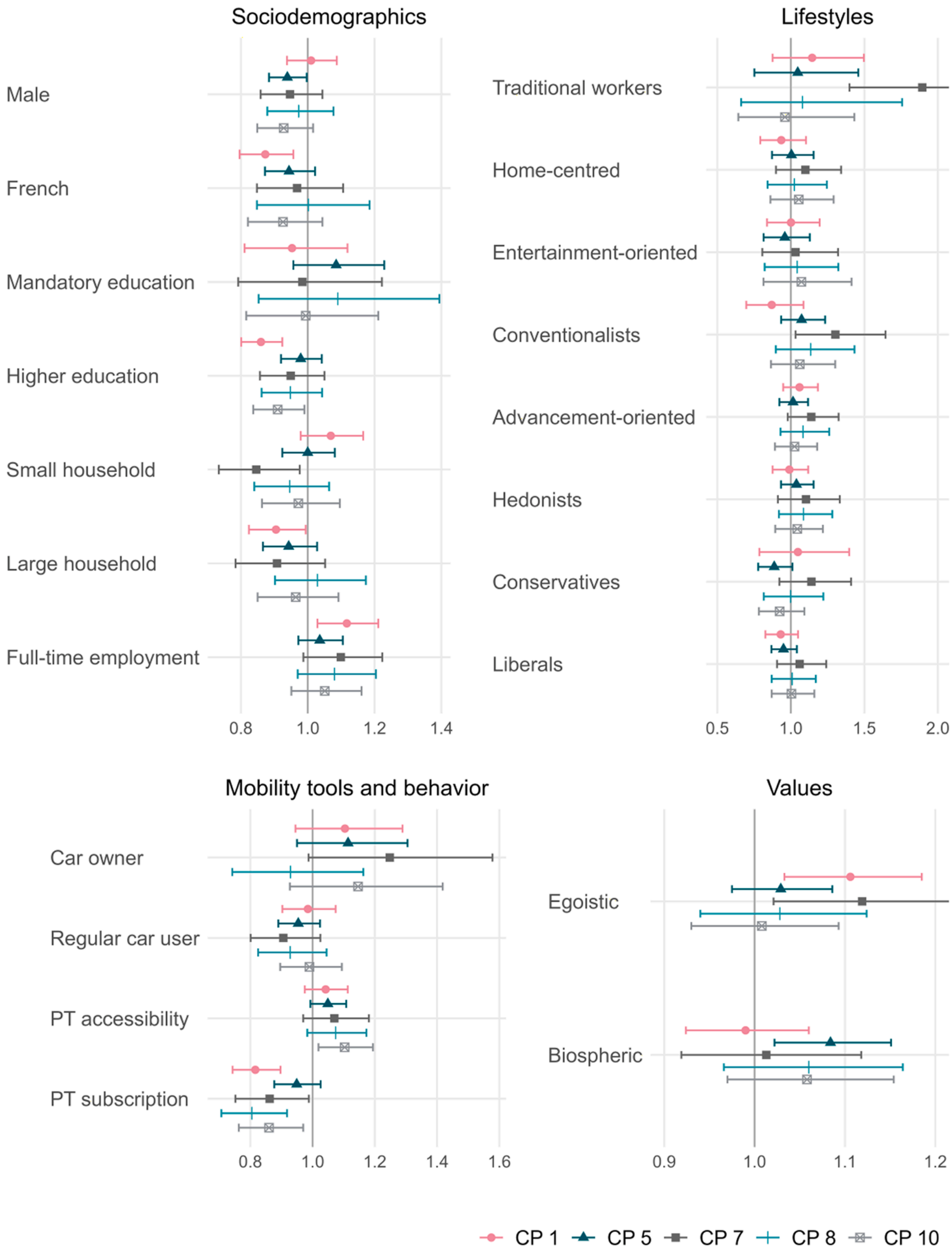

Fig. 7. Response heterogeneity. *Notes*: Error bars represent 95 % confidence intervals. The reference categories (in order) are: female, German-speakers, secondary education, household with 3 members, not working full time, not owning a car, using the car on <3 days per week, living in a zip code that does not have "high PT access" as defined by an index, not holding a PT subscription, belonging to the lifestyle category "Reflexives", and having a below-median index for "egoistic" and "biospheric" values. The coefficient estimates are shown in Table A.5.

demographics (gender, age, language, household size, income, education, employment); variables capturing mobility tool ownership and habits (access to PT and road network; PT subscription and car ownership; regular use of car, PT or bicycle); personal values; and lifestyles (see above). One category is always omitted as it will be captured by the constant (reference category). Note that Z_i is not included by itself as it would be absorbed by the person fixed-effects μ_i. Because we are not interested in a variation across "non-personal" variables that were identified by the CF as relevant, such as the weather or zip codes, we do not include these in Z_i.

We start by estimating the full model and then gradually reduce its scope by eliminating variables for which the interactions with the ten COVID periods do not meet a threshold for a joint significance test.[20] After estimation, we remove the variables that have a joint p-value of more than 0.4. We then re-estimate the model and proceed to make cuts at $p = 0.3$ and, finally, at $p = 0.2$.[21] The final model includes 21 interaction variables, which are shown in Fig. 7. For exposition purposes, we only include the results for 5 of the 10 COVID periods; the full results are shown in Table A.5 in the appendix.

The results of the heterogeneity analysis can be summarized as follows. Starting with the top left panel in the figure, we see that men reduced their travel distances somewhat more than women, but only in the later periods of the pandemic. Since these are the results of a multivariate regression, this result is conditional on the other included variables (i.e., this effect is not due to a higher employment rate or a different education level among men). For residents of the French-speaking part of Switzerland, the opposite is the case: They reduced travel more than German speakers during CP1, but not thereafter. This would be consistent with French-speaking residents being more likely to follow the appeal of the federal government to reduce travel as much as possible.

The reduction in distance traveled was particularly pronounced for people with a tertiary education (who are more likely to be able to work from home) and those living in large households. The latter result is likely due to the presence of children, which is important due to school closures during the first wave. As could be expected, those with full employment reduced their travel by less than those who do not work, or who work part-time only.

In the panel on the lower left, we see that owning a car is associated with a lower reduction of travel during the pandemic, as could be expected. We find that the participants holding a public transport subscription reduced travel by more than those that do not.[22] This is consistent with the result that PT is the most-affected mode (as regular PT users tend to have a subscription). On the other hand, living in a postcode with high access to PT is associated with a lower-than normal reduction in mobility. This is not as expected, but it is possible that "PT accessibility" is correlated with urban density, which is not reflected in our data, and which may be associated with increased mobility during the pandemic.

The lifestyle category assigned to the respondents also explained a significant part of the response heterogeneity (upper right). Over all CPs combined, "Conservatives" reduced their travel by more than the reference category ("Reflexives"), whereas "Traditional workers" reduced it by less, presumably due to a limited flexibility in work hours and options to work from home.

Last, we find that respondents that scored highly on the values dimensions "biospheric" and "egoistic" traveled more than others during the pandemic. Whereas the reason for the former is somewhat unclear, the latter is consistent with the interpretation of reducing mobility as a public good during the pandemic as egoists are less likely to contribute towards a public good.

6. Discussion and conclusions

Using tracking data collected through a smartphone-based that includes pre- and post-pandemic information on the same people, we find that panel participants reduced their total distance traveled by an average of 60 percent after the onset of the pandemic. This is a large reduction considering that the Swiss federal government never imposed a formal stay-at-home rule, but instead appealed to the population to act "responsibly" meaning to stay at home if possible. The reduction in travel was therefore a combination of policy, voluntary firm measures and people choosing not to travel in the face of the virus threat. Other researchers also identify the role of voluntary measures and individual response in reducing mobility (Maloney and Taskin, 2020; Yabe et al., 2020). The Swiss case shows that individual mobility can be significantly reduced without the formal travel bans that have been instituted in many other countries.

We observe that people rapidly responded to the new conditions. Large adjustments in activities, work routines and transport patterns took place almost overnight, implying that many people are willing and able to make important changes to their lives if there is a clear need, and even if they are not obliged to do so by law. Our findings are consistent with Hong et al. (2022), who show that people rapidly adjusted to a new and stable transport patterns. The observation that people can and do change their habits may provide some hope for other challenges that require transformational adjustments, for example in the context of climate change.

Travel distances increased as the economy was re-opened, but the recovery was incomplete and differed across the different modes of transport. This is consistent with observations elsewhere (see, e.g., Beck et al., 2020). Whereas driving distances are more or less back at pre-pandemic levels, public transport continues to be under-used at the end of our sample period. Remarkably, the introduction of a mask mandate did not have a measurable effect on public transport ridership. If and when most firms return to workplace presence, the reluctance to use public transport suggests a threat of increased road congestion if the average daily traveled kilometers return to their pre-pandemic levels without a corresponding return to public transport (Hu et al., 2020; Li et al., 2021). However, it is also

[20] The number of the dummies tested jointly depends on the dimension in question. For the gender dimension, we include 10 interaction terms (one "male" dummy multiplied by each CP), and test these 10 coefficients jointly. For lifestyles, the resulting number of coefficients is 80, as there are 8 separate lifestyle dummies included in the model (the ninth serving as the reference).

[21] Among others, this procedure dropped variables related to income, age and the two values dimensions "altruistic" and "hedonic".

[22] By "subscription" we mean either a "general abonnement" allowing for unrestricted use of the Swiss transport system or a line- or region-specific transport pass.

possible that a permanent shift towards work from home will take place, which could more than offset the increase in private car usage (Beck et al., 2020; Beck and Hensher, 2021).

One might worry that in response to having to cut work-related travel, people may (over-)compensate by increasing their demand for leisure travel. During a period of relative safety between the first two waves, the panel members indeed increased their driving distances during week-ends, which could be a sign of "catching up" with leisure trips that had to be canceled during the early phase of the pandemic. However, for all other periods we see no increase of travel during the weekends, relative to the pre-pandemic situation. We therefore conclude that over-compensation was not a significant problem in the Swiss transport sector during the pandemic. This is good news also for future crises, if and when they arise.

The mobility response to the second wave was qualitatively very different from the first wave. Although infection rates were significantly higher, the decrease in the distance traveled was much less pronounced, implying that people were reluctant to limit their activity to the same degree, and / or that the opportunity cost of reducing certain activities increases more than proportionally with time. For this reason, it becomes increasingly difficult to contain personal mobility, and thus a pandemic wave, at least without imposing draconian measures. Note that the re-opening of economic and public life occurred before a significant share of the Swiss population had been vaccinated. This is yet another argument in favor of a quick roll-out of vaccinations to make society more robust to a lowering of the "pandemic guard" that may turn out to be premature.

We measure a significant heterogeneity of travel responses to the pandemic. It is evident that the capacity for an individual response is restricted by socio-demographic factors such as the type of profession or the family situation. People with a tertiary education reduced their travel (and thus their risk of infection) by more than others, along with households with children and regular PT users. Car ownership also plays an important role as a predictor of individual responses to the pandemic and the policy measures. Other researchers have observed similar differences across socio-economic groups (Bonaccorsi et al., 2020; Abdullah et al., 2020; Barbieri et al., 2021). In addition to the more standard socio-economic characteristics, we find that the decision to stay at home is determined at least partly by personal values and lifestyles. The finding that people who score high on the "egoistic" index (or low on its counterpart "altruistic") are less willing to contribute to the public good by reducing travel in the midst of a pandemic may be intuitive, but it is nevertheless an important finding as it suggests that relying on people's own sense of responsibility may not be sufficient in the presence of important external costs.

Income itself was not significant in our multi-variate regressions, but it is correlated with some of the identified predictors for the variation in the pandemic response such as education and household size. The distributional implications of the pandemic and of the governmental measures in terms of the consequences for individual behavior should therefore be considered when implementing public policy for future pandemics. For example, pandemic relief measures should be means-tested, schools left open as long as possible, and an increased (decreased) response by PT users (car owners) should be anticipated.

Policymakers face a trade-off between containing a pandemic in the short run and the long-term costs associated with changes in mobility behavior (in particular of increased car usage at the expense of PT) with regard to climate goals in the transport sector. To make public transport more "pandemic-resistant" in the future, additional investments may be needed such as improved air filtration systems or automatic temperature detection devices in public transport. This would not only protect the revenues of public transport providers, but also improve the outlook for a decarbonization of the transport sector.

Future research is needed to investigate the long-term impact of the pandemic on public transport use, but also the impact of working from home and other remote-flexible work arrangements that are currently being introduced by firms worldwide. It is possible that such new work arrangements will lead to a different pattern of travel demand across space, time and modes. This would require new approaches in transport policy and different investments in transport infrastructure. New work arrangements may furthermore impact relevant outcomes besides transport, such as impact workers' productivity, the identification of workers with their employer and people's work-life-balance.

CRediT authorship contribution statement

Beat Hintermann: Funding acquisition, Conceptualization, Methodology, Formal analysis, Writing – review & editing. **Beaumont Schoeman:** Methodology, Formal analysis, Visualization, Writing – original draft. **Joseph Molloy:** Conceptualization, Software, Writing – original draft. **Thomas Schatzmann:** Data curation, Writing – original draft. **Christopher Tchervenkov:** Software, Data curation. **Kay W. Axhausen:** Funding acquisition, Conceptualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See Fig. A1 and Tables A1–A5.

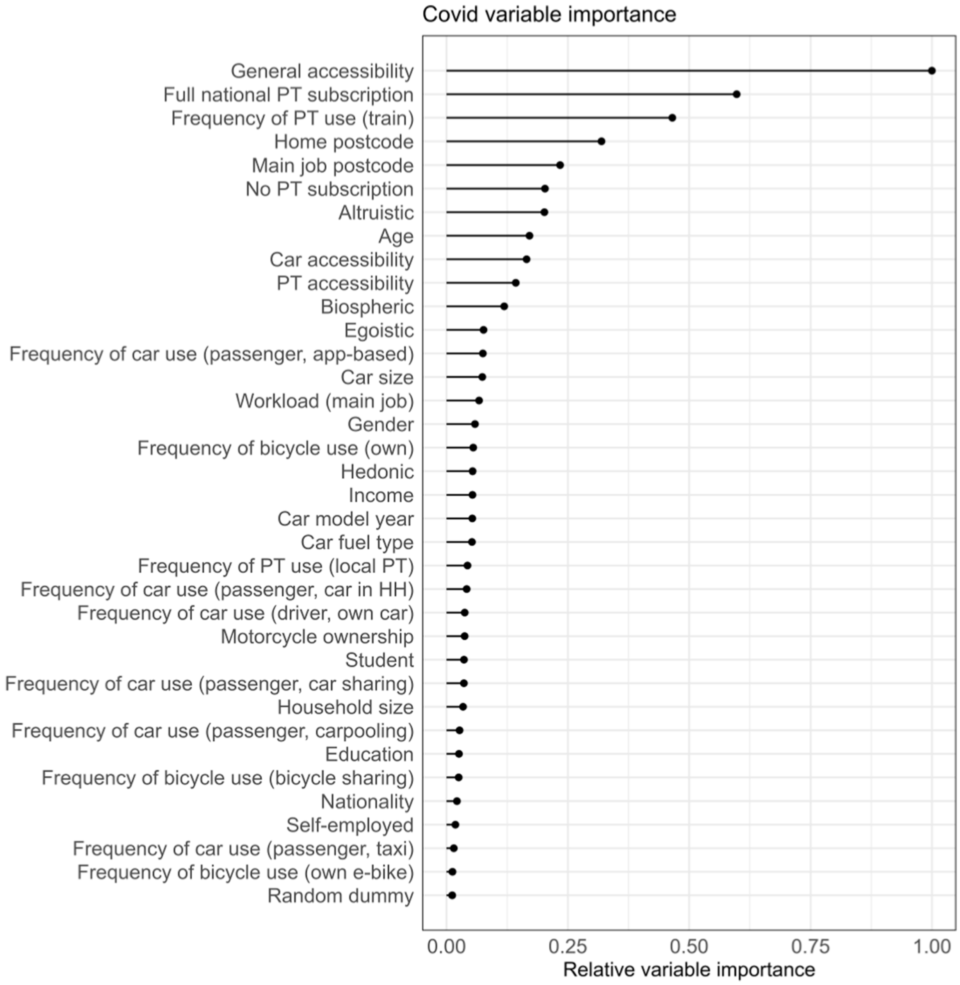

Fig. A1. Variable importance from CF approach for entire COVID period. *Notes:* The figure shows variable importance measure from the causal forest approach using the baseline period and the entire COVID period. The variable importance is normalised relative to the “most important” variable. For more information about the included variables, refer to Tables 1, 2 and A.1.

Table A1
Additional descriptive statistics for MobisCovid sample.

Variable	Subcategory	Level	Value
Car characteristics	Fuel	Gasoline	58.9 %
		Diesel	33.8 %
		Hybrid (gasoline/diesel + electric)	4.6 %
		Electric	2.1 %
		Other	0.5 %
	Model year	2015 or later	43.5 %
		2011–2014	28.5 %
		2006–2010	19.0 %
		2001–2005	5.9 %
		1997 – 2000	1.8 %

(continued on next page)

Table A1 (*continued*)

Variable	Subcategory	Level	Value
		Don't know	1.0 %
		1993–1996	0.2 %
		1992 or earlier	0.1 %
	Size	Medium to large	47.4 %
		Small	25.5 %
		Off-road	16.5 %
		Minivan	8.4 %
		Luxury or sports coupe	2.3 %
Mobility tool use		Regular car user	72.1 %
		Regular PT user	26.3 %
		Regular bicycle user	14.3 %
PT subscription		Full or regional subscription	22.1 %
Mobility access		High general access	38.8 %
		High car access	39.7 %
		High PT access	41.7 %
Lifestyle		Advancement-oriented	30.9 %
		Liberals	20.0 %
		Hedonists	16.8 %
		Reflexives	14.0 %
		Home-centred	8.2 %
		Entertainment-oriented	5.0 %
		Conventionalists	2.4 %
		Conservatives	1.5 %
		Traditional workers	1.1 %
Values		Altruistic	64.5 %
		Egoistic	61.6 %
		Hedonic	56.9 %
		Biospheric	67.5 %
Employment		Full-time	71.3 %

Notes: Additional descriptive statistics for variables used in causal forest analysis and regressions using the MOBIS sample (n = 1,649), since the LINK sample does not include all the additonal demographic variables available in the MOBIS dataset. The "Values" variables are measured on a continuous scale and individuals with a value above the median are assigned the respective "Value". As a result, an individual can have more than one "Value".

Table A2
Effect of the pandemic on total travel distance.

	Overall margin	Overall margin	Intensive margin	Extensive margin
Week 0	0.820*	0.796*	0.795*	0.009
Week 1	0.443*	0.436*	0.512*	−0.117*
Week 2	0.450*	0.412*	0.463*	−0.104*
Week 3	0.489*	0.428*	0.457*	−0.073*
Week 4	0.535*	0.482*	0.509*	−0.059*
Week 5	0.535*	0.498*	0.528*	−0.063*
Week 6	0.594*	0.586*	0.613*	−0.048*
Week 7	0.586*	0.608*	0.627*	−0.035*
Week 8	0.697*	0.671*	0.690*	−0.036*
Week 9	0.695*	0.674*	0.688*	−0.026*
Week 10	0.857′	0.818*	0.824*	−0.012*
Week 11	0.870*	0.791*	0.806*	−0.025*
Week 12	0.829*	0.839*	0.853*	−0.018*
Week 13	0.824*	0.859*	0.861*	−0.005
Week 14	0.888*	0.882*	0.906*	−0.034*
Week 15	0.951′	0.990	1.003	−0.017*
Week 16	0.948	0.941°	0.960	−0.027*
Week 17	0.971	0.965	0.984	−0.022*
Week 18	0.968	0.947°	0.971	−0.032*
Week 19	0.983	1.034	1.069′	−0.041*
Week 20	0.961	1.116°	1.169*	−0.052*
Week 21	0.967	1.003	1.052	−0.056*
Week 22	0.949	1.036	1.056	−0.025*
Week 23	0.947	1.015	1.023	−0.008
Week 24	0.913*	0.960	0.972	−0.021*
Week 25	0.939	0.963	0.985	−0.022*
Week 26	0.937′	0.913*	0.949	−0.047*
Week 27	0.931′	0.975	0.994	−0.029*
Week 28	0.876*	0.918*	0.939*	−0.024*

(*continued on next page*)

Table A2 (*continued*)

	Overall margin	Overall margin	Intensive margin	Extensive margin
Week 29	0.885*	0.904*	0.938′	−0.043*
Week 30	0.870*	0.906′	0.960	−0.059*
Week 31	0.879*	0.908′	0.949	−0.054*
Week 32	0.825*	0.825*	0.877*	−0.061*
Week 33	0.751*	0.772*	0.823*	−0.068*
Week 34	0.693*	0.716*	0.771*	−0.074*
Week 35	0.752*	0.728*	0.778*	−0.071*
Week 36	0.740*	0.709*	0.758*	−0.071*
Week 37	0.749*	0.748*	0.783*	−0.055*
Week 38	0.695*	0.700*	0.741*	−0.065*
Week 39	0.698*	0.703*	0.741*	−0.060*
Week 40	0.720*	0.728*	0.775*	−0.068*
Week 41	0.680*	0.688*	0.753*	−0.079*
Week 42	0.651*	0.661*	0.728*	−0.090*
Week 43	0.678*	0.641*	0.691*	−0.076*
Week 44	0.621*	0.605*	0.661*	−0.084*
Week 45	0.646*	0.624*	0.682*	−0.081*
Week 46	0.577*	0.586*	0.649*	−0.088*
Week 47	0.624*	0.649*	0.721*	−0.093*
Week 48	0.732*	0.673*	0.724*	−0.077*
Week 49	0.780*	0.721*	0.770*	−0.069*
Week 50	0.796*	0.762*	0.801*	−0.062*
Week 51	0.735*	0.712*	0.754*	−0.060*
Week 52	0.705*	0.694*	0.745*	−0.073*
Week 53	0.698*	0.672*	0.719*	−0.070*
Week 54	0.779*	0.712*	0.756*	−0.061*
Week 55	0.831*	0.759*	0.809*	−0.068*
Week 56	0.788*	0.753*	0.803*	−0.066*
Week 57	0.764*	0.729*	0.781*	−0.072*
Week 58	0.794*	0.711*	0.758*	−0.064*
Week 59	0.741*	0.755*	0.806*	−0.066*
Week 60	0.792*	0.741*	0.794*	−0.069*
Week 61	0.811*	0.841*	0.886*	−0.059*
Week 62	0.871*	0.850*	0.882*	−0.041*
Week 63	0.794*	0.755*	0.802*	−0.057*
Weekend	0.995	0.851*	0.907*	−0.061*
Heat		0.972*	0.973*	−0.001°
Cold		1.006*	1.006*	−0.001*
Precipitation		1.001	1.001	−0.001*
Sunshine		1.007*	1.007*	0.000*
Weekend × Heat		0.969′	0.971′	−0.001
Weekend × Cold		1.006′	1.006′	0.001*
Weekend × Precipitation		1.001	1.002	0.000
Weekend × Sunshine		1.021*	1.018*	0.002*
Pseudo R^2	0.203	0.206	0.214	
N	368,886	368,861	335,304	363,900
Participants	1,649	1,649	1,649	1,649

Notes: *: $p < 0.01$, ’: $p < 0.05$, °: $p < 0.1$. Standard errors are clustered by person and day. The overall and intensive margins are estimated using a PPML model. The coefficients have been exponentiated to derive proportional effects relative to the baseline (a value of 1.00 indicates no effect). The results shown for the extensive margin are the marginal effects from a Logit regression. For a definition of overall, intensive and extensive margins, see main text.

Table A3
Effect of the pandemic on different modes.

	Car			Public Transport			Walking			Bicycle		
	Overall	Intensive	Extensive	Overall	Intensive	Extensive	Overall	Intensive	Extensive	Overall	Intensive	Extensive
Week 0	0.807*	0.814*	−0.006	0.729’	0.884	−0.042*	0.987	0.988	0.017’	0.962	0.897	−0.001
Week 1	0.501*	0.729*	−0.226*	0.096*	0.413*	−0.225*	0.666*	0.827*	−0.009	0.871	1.022	−0.165*
Week 2	0.478*	0.669*	−0.214*	0.082*	0.499*	−0.285*	0.644*	0.773*	−0.032*	0.775	0.935	−0.164*
Week 3	0.486*	0.628*	−0.173*	0.092*	0.515*	−0.271*	0.698*	0.795*	−0.012*	0.891	0.939	−0.132*
Week 4	0.539*	0.687*	−0.161*	0.067*	0.354*	−0.255*	0.755*	0.855*	0.026*	1.598*	1.136°	−0.121*
Week 5	0.546*	0.691*	−0.159*	0.117*	0.534*	−0.253*	0.839*	0.948	0.025*	1.662*	1.206*	−0.119*
Week 6	0.659*	0.793*	−0.135*	0.135*	0.589*	−0.239*	0.868*	0.958	0.048*	2.264*	1.335*	−0.105*
Week 7	0.700*	0.786*	−0.087*	0.160*	0.510*	−0.213*	0.874’	0.959	0.021*	1.793*	1.305*	−0.090*
Week 8	0.780*	0.855*	−0.073*	0.177*	0.527*	−0.190*	0.818*	0.892*	0.031*	1.885*	1.259*	−0.094*
Week 9	0.794*	0.846*	−0.049*	0.211*	0.585*	−0.176*	0.792*	0.861*	0.016*	1.412*	1.109°	−0.081*
Week 10	0.939	0.976	−0.039*	0.291*	0.613*	−0.142*	0.945	0.998	0.041*	1.690*	1.155*	−0.056*
Week 11	0.924’	0.943°	−0.021*	0.296*	0.664*	−0.138*	0.843*	0.900’	0.031*	1.360*	1.059	−0.066*
Week 12	0.963	1.002	−0.035*	0.371*	0.720*	−0.118*	0.924°	0.982	0.037*	1.602*	1.210*	−0.057*
Week 13	0.970	0.989	−0.020*	0.434*	0.757*	−0.105*	0.967	0.990	0.045*	1.903*	1.213*	−0.037*
Week 14	0.994	1.031	−0.034*	0.469*	0.791*	−0.099*	0.925’	0.981	0.044*	1.780*	1.187*	−0.063*
Week 15	1.105’	1.134*	−0.019*	0.562*	0.877’	−0.084*	1.057	1.105’	0.051*	1.860*	1.200*	−0.046*
Week 16	1.071°	1.069°	−0.002	0.492*	0.776*	−0.083*	0.979	1.048	0.047*	1.901*	1.206*	−0.065*
Week 17	1.092°	1.114*	−0.018’	0.495*	0.778*	−0.087*	0.967	1.026	0.057*	2.045*	1.251*	−0.050*
Week 18	1.070’	1.097*	−0.028*	0.522*	0.809*	−0.083*	0.956	1.038	0.046*	1.846*	1.234*	−0.078*
Week 19	1.204*	1.250*	−0.030*	0.498*	0.824’	−0.098*	1.046	1.125*	0.043*	1.932*	1.287*	−0.076*
Week 20	1.298*	1.397*	−0.046*	0.538*	0.937	−0.103*	1.240’	1.325*	0.031*	1.863*	1.354*	−0.082*
Week 21	1.171’	1.238*	−0.042*	0.466*	0.808’	−0.102*	1.073	1.154*	0.013’	1.415’	1.246*	−0.080*
Week 22	1.173*	1.231*	−0.034*	0.538*	0.833’	−0.088*	1.133’	1.168’	0.035*	1.907*	1.300*	−0.047*
Week 23	1.095	1.131’	−0.023*	0.642*	0.904	−0.073*	1.019	1.037	0.040*	1.777*	1.228*	−0.028*
Week 24	1.024	1.044	−0.023*	0.622*	0.916	−0.076*	0.936	0.959	0.045*	1.834*	1.184°	−0.029*
Week 25	1.030	1.074	−0.034*	0.693*	0.902	−0.063*	1.038	1.054°	0.041*	1.552*	1.049	−0.030*
Week 26	0.986	1.056	−0.055*	0.634*	0.912	−0.074*	0.926	0.977	0.033*	1.487*	1.153°	−0.062*
Week 27	1.043	1.080’	−0.030*	0.654*	0.865’	−0.064*	0.980	1.017	0.049*	1.833*	1.239*	−0.047*
Week 28	0.986	1.018	−0.031*	0.630*	0.916	−0.065*	0.938	0.971	0.037*	1.815*	1.195’	−0.039*
Week 29	0.985	1.022	−0.032*	0.601*	0.873	−0.069*	0.956	0.982	0.021*	1.402’	1.169°	−0.040*
Week 30	0.988	1.057°	−0.053*	0.586*	0.921	−0.079*	0.953	1.000	0.010	1.213	1.117	−0.054*
Week 31	0.967	1.026	−0.052*	0.662*	0.941	−0.078*	0.986	1.006	0.021*	1.164	0.947	−0.032*
Week 32	0.912’	1.004	−0.073*	0.489*	0.792*	−0.106*	1.009	1.035	0.010°	1.078	1.027	−0.033*
Week 33	0.868*	0.965	−0.082*	0.403*	0.740*	−0.106*	0.961	0.999	−0.001	1.088	1.092	−0.049*
Week 34	0.834*	0.937*	−0.093*	0.264*	0.584*	−0.140*	0.953	1.004	0.011’	1.149	1.047	−0.055*
Week 35	0.816*	0.910’	−0.087*	0.374*	0.819*	−0.135*	0.937	0.979	0.007	1.146	1.074	−0.050*
Week 36	0.795*	0.864*	−0.075*	0.423*	0.759*	−0.118*	0.828*	0.875*	−0.020*	0.670’	0.901	−0.056*
Week 37	0.831*	0.891*	−0.062*	0.453*	0.836°	−0.117*	0.847*	0.887*	−0.018*	0.711’	0.876°	−0.053*
Week 38	0.764*	0.839*	−0.078*	0.463*	0.752*	−0.103*	0.864*	0.905*	−0.037*	0.456*	0.726*	−0.052*
Week 39	0.798*	0.864*	−0.062*	0.371*	0.704*	−0.126*	0.844*	0.888’	−0.037*	0.508*	0.779*	−0.052*
Week 40	0.828*	0.928’	−0.082*	0.372*	0.719*	−0.126*	0.891*	0.948	−0.035*	0.659*	0.992	−0.064*
Week 41	0.775*	0.900*	−0.094*	0.331*	0.729’	−0.147*	0.879°	0.976	−0.033*	0.681	0.940	−0.093*
Week 42	0.769*	0.942	−0.128*	0.218*	0.652’	−0.191*	0.967	1.055	−0.028*	0.819	1.000	−0.090*
Week 43	0.731*	0.828*	−0.098*	0.310*	0.674*	−0.151*	0.827*	0.891’	−0.036*	0.638*	0.959	−0.072*
Week 44	0.664*	0.801*	−0.133*	0.357*	0.760*	−0.144*	0.820*	0.883*	−0.051*	0.409*	0.775’	−0.071*
Week 45	0.696*	0.826*	−0.117*	0.337*	0.815°	−0.161*	0.900’	0.950	−0.031*	0.601*	0.877°	−0.064*
Week 46	0.668*	0.805*	−0.131*	0.277*	0.676*	−0.157*	0.824*	0.905	−0.048*	0.428*	0.867	−0.088*

(*continued on next page*)

Table A3 (*continued*)

	Car			Public Transport			Walking			Bicycle		
	Overall	Intensive	Extensive	Overall	Intensive	Extensive	Overall	Intensive	Extensive	Overall	Intensive	Extensive
Week 47	0.740*	0.889*	−0.123*	0.283*	0.659*	−0.155*	0.898°	0.977	−0.027*	0.920	1.158	−0.087*
Week 48	0.767*	0.858*	−0.088*	0.314*	0.648*	−0.150*	0.805*	0.859*	−0.044*	0.783	1.378’	−0.071*
Week 49	0.796*	0.898’	−0.087*	0.359*	0.732*	−0.144*	1.017	1.078	0.023*	1.386*	1.138	−0.073*
Week 50	0.824*	0.918’	−0.089*	0.396*	0.771*	−0.125*	1.081	1.126’	0.024*	1.606*	1.210’	−0.051*
Week 51	0.788*	0.894*	−0.091*	0.325*	0.581*	−0.102*	0.991	1.017	0.009	1.313’	1.201’	−0.039*
Week 52	0.779*	0.887*	−0.094*	0.346*	0.609*	−0.118*	0.893*	0.935°	−0.016*	0.926	1.069	−0.059*
Week 53	0.754*	0.846*	−0.086*	0.361*	0.694*	−0.123*	0.811*	0.857*	−0.042*	0.565*	0.883°	−0.068*
Week 54	0.803*	0.899*	−0.081*	0.324*	0.647*	−0.112*	0.889*	0.926*	−0.009°	0.993	1.145	−0.050*
Week 55	0.869*	0.966	−0.078*	0.319*	0.605*	−0.111*	0.906°	0.945	−0.002	1.215	1.225*	−0.044*
Week 56	0.856*	0.954	−0.077*	0.348*	0.672*	−0.111*	0.906°	0.954	−0.018*	0.941	1.122	−0.064*
Week 57	0.820*	0.916’	−0.086*	0.423*	0.750*	−0.079*	0.805*	0.855’	−0.037*	0.589*	0.953	−0.071*
Week 58	0.806*	0.887*	−0.071*	0.354*	0.683*	−0.091*	0.834*	0.876’	−0.012’	1.009	1.117	−0.050*
Week 59	0.850*	0.952	−0.078*	0.399*	0.697*	−0.093*	0.948	0.992	−0.014’	0.957	1.093	−0.053*
Week 60	0.855*	0.928°	−0.061*	0.374*	0.689*	−0.098*	0.856’	0.901	−0.014’	0.962	1.050	−0.053*
Week 61	0.952	1.038	−0.065*	0.433*	0.701*	−0.089*	1.040	1.073	−0.011	1.215	1.259°	−0.044*
Week 62	0.948	0.993	−0.041*	0.484*	0.799°	−0.075*	0.955	0.971	−0.017*	1.125	1.249°	−0.025*
Week 63	0.860*	0.965	−0.079*	0.369*	0.719*	−0.089*	0.958	1.004	0.000	1.098	1.064	−0.052*
Weekend	0.918’	1.006	−0.064*	0.603*	0.947	−0.076*	0.975	1.078’	−0.041*	0.807°	1.071	−0.087*
Heat	0.964*	0.962*	0.000	1.006	1.004	0.000	0.950*	0.953*	0.001’	0.990	0.981’	−0.001
Cold	1.007*	1.007*	−0.001*	1.002	0.998	0.001*	1.016*	1.015*	0.001*	1.016	1.008°	0.001’
Precipitation	1.002°	1.002°	0.000°	0.999	1.000	0.000	0.996*	0.997*	−0.001*	0.981*	0.996	−0.001*
Sunshine	1.005*	1.007*	−0.001*	1.006°	1.007*	−0.001*	1.016*	1.014*	0.004*	1.065*	1.024*	0.001*
Weekend × Heat	0.975°	0.972’	0.001	0.996	0.997	−0.003	0.944*	0.955*	−0.002	0.963	0.993	−0.006*
Weekend × Cold	1.006’	1.009*	−0.001*	0.998	1.000	−0.001*	1.006’	1.004	0.002*	1.021’	0.999	0.001*
Weekend × Precip.	1.001	1.002	−0.001’	0.994	1.000	−0.001*	1.000	1.001	0.001*	1.019°	1.006	−0.000
Weekend × Sunshine	1.016*	1.015*	0.001*	1.008	1.005	0.001*	1.024*	1.019*	0.004*	1.055*	1.020*	0.003*
Pseudo R^2	0.207	0.206		0.378	0.440		0.207	0.215		0.410	0.506	
N	368,861	259,127	368,814	366,384	75,522	366,384	368,861	287,054	334,281	334,281	38,389	368,415
Participants	1,649	1,649		1,630	1,607		1,649	1,649		1,432	1,293	

Notes: *: $p < 0.01$, ’: $p < 0.05$, °: $p < 0.1$. Standard errors are clustered by person and day. The overall and intensive margins are estimated using a PPML model with distance by the respective mode as the dependent variable. The coefficients have been exponentiated to derive proportional effects relative to the baseline (a value of 1.00 indicates no effect). The results shown for the extensive margin are the marginal effects from a Logit regression. For a definition of overall, intensive and extensive margins, see main text.

Table A4
Relative relevance of government measures and infection rates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CP1	0.512*	0.552*	0.484*	0.624*	0.094*	1.421*	0.712*
CP2	0.616*	0.639*	0.606*	0.747*	0.161*	1.478*	0.746*
CP3	0.735*	0.770*	0.727*	0.884*	0.273*	1.216′	0.771*
CP4	0.852*	0.875*	0.840*	0.972	0.457*	1.614*	0.917*
CP5	0.931*	0.958′	0.893*	1.050°	0.526*	1.760*	0.963
CP6	0.552*	0.540*	0.752*	0.601*	0.325*	0.939	0.863′
CP7	0.528*	0.510*	0.679*	0.592*	0.235*	0.95	0.927
CP8	0.594*	0.586*	0.675*	0.661*	0.300*	1.248	0.909′
CP9	0.631*	0.648*	0.723*	0.712*	0.318*	0.97	0.871*
CP10	0.665*	0.677*	0.754*	0.754*	0.344*	0.942	0.922′
Weekend	0.820*	0.954′	0.820*	0.914′	0.586*	0.790°	0.920′
CP1 × Weekend	0.966	1.004	0.967	0.797*	0.827	1.662*	1.322*
CP2 × Weekend	1.102	1.059	1.103°	0.966	1.103	1.527′	1.340*
CP3 × Weekend	1.127′	1.168′	1.126′	1.007	1.195	1.367′	1.311*
CP4 × Weekend	1.158*	1.131′	1.154*	1.093°	1.306′	1.07	1.087
CP5 × Weekend	1.128*	1.065′	1.126*	1.079°	1.157	0.969	1.076
CP6 × Weekend	0.948	0.958	0.951	0.880*	0.923	1.124	1.190*
CP7 × Weekend	0.961	1.008	0.966	0.879′	1.23	0.824	0.972
CP8 × Weekend	1.069	1.144°	1.062	1.014	0.926	0.953	1.150′
CP9 × Weekend	1.016	1.054	1.024	0.954	0.881	1.380°	1.106′
CP10 × Weekend	1.065	1.141′	1.051	0.992	1.194	1.483′	1.01
Heat	0.985*		0.987*	0.984*	1.005	0.966*	0.957*
Cold	0.999		0.999	1.000	0.999	0.997	1.010*
Precipitation	1.000		1.000	1.001	1.000	0.979*	0.995*
Sunshine	1.010*		1.010*	1.006*	1.008*	1.078*	1.020*
Weekend × Heat	0.962′		0.962′	0.962′	0.974	1.015	0.969°
Weekend × Cold	1.012*		1.012*	1.012*	1.004	1.021°	1.009′
Weekend × Precip.	1.001		1.001	1.001	0.994	1.019°	1.001
Weekend × Sunshine	1.016*		1.016*	1.015*	1.001	1.030*	1.013*
Infections	0.873*	0.851*		0.837*	1.240°	0.502*	0.886*
Infections^2	1.036′	1.043*		1.046*	0.967	1.151*	1.028′
Infections × Wave 2	1.284*	1.325*		1.362*	0.896	1.816*	1.118′
Infections^2 × Wave 2	0.958*	0.951*		0.948*	1.024	0.878*	0.975′
Marg. effect Wave 1	0.923*	0.910*		0.899*	1.177′	0.627*	0.925*
Marg. effect Wave 2	1.119*	1.126*		1.140*	1.088	0.956	0.999
N	368,861	368,886	368,861	368,861	366,384	334,281	368,861
Participants	1,649	1,649	1,649	1,649	1,630	1,432	1,649
BIC	1.55×101^{0}	1.56×10^{10}	1.55×10^{10}	1.53×10^{10}	6.69×10^{9}	1.37×10^{9}	9.93×10^{8}
Pseudo-R^2	0.205	0.202	0.205	0.207	0.377	0.407	0.207

Notes: *: $p < 0.01$, ’: $p < 0.05$, °: $p < 0.1$. Standard errors are clustered by person and day. Model (1) is the full model. The marginal effects for waves 1 and 2 are functions of the infection-related regression coefficients. Models (2) and (3) are reduced versions that omit the weather and infections. Models (4)–(7) use distance by car, PT, bicycle, and walking as dependent variables, respectively.

Table A5
Effect heterogeneity: Final model.

Variable	CP1	CP2	CP3	CP4	CP5	CP6	CP7	CP8	CP9	CP10
Male	1.010	0.937	0.958	1.003	0.939′	0.974	0.947	0.973	0.921°	0.928
	(0.038)	(0.038)	(0.036)	(0.035)	(0.029)	(0.041)	(0.047)	(0.050)	(0.042)	(0.043)
Education (Tertiary)	0.860*	0.860*	0.877*	0.916′	0.979	0.917′	0.949	0.948	0.941	0.910′
	(0.032)	(0.035)	(0.031)	(0.033)	(0.031)	(0.039)	(0.049)	(0.046)	(0.040)	(0.039)
Education (Primary)	0.953	0.953	1.068	1.076	1.085	0.982	0.984	1.090	1.058	0.994
	(0.078)	(0.082)	(0.076)	(0.070)	(0.069)	(0.089)	(0.109)	(0.137)	(0.107)	(0.100)
Large Household	0.905′	0.845*	0.928	0.912°	0.943	0.942	0.908	1.029	0.981	0.964
	(0.043)	(0.044)	(0.045)	(0.046)	(0.041)	(0.054)	(0.068)	(0.069)	(0.061)	(0.062)
Small Household	1.069	1.037	1.009	1.009	1.000	0.961	0.846′	0.946	1.026	0.972
	(0.048)	(0.051)	(0.045)	(0.048)	(0.040)	(0.051)	(0.062)	(0.057)	(0.058)	(0.059)
Full-time job	1.117*	1.119*	1.112*	1.043	1.036	1.122*	1.099°	1.080	1.080	1.051
	(0.046)	(0.049)	(0.044)	(0.040)	(0.034)	(0.048)	(0.060)	(0.060)	(0.052)	(0.053)
French Speaker	0.873*	0.925	0.968	0.930°	0.944	1.010	0.968	1.002	1.000	0.926
	(0.041)	(0.046)	(0.041)	(0.036)	(0.038)	(0.062)	(0.066)	(0.086)	(0.064)	(0.057)
PT Subscription	0.816*	0.826*	0.805*	0.855*	0.949	0.890′	0.862′	0.805*	0.854*	0.860′
	(0.039)	(0.043)	(0.037)	(0.039)	(0.038)	(0.049)	(0.060)	(0.054)	(0.051)	(0.053)
Car Owner	1.104	1.216′	1.210′	1.191′	1.114	0.975	1.248°	0.929	0.977	1.146
	(0.087)	(0.103)	(0.095)	(0.095)	(0.090)	(0.094)	(0.149)	(0.106)	(0.102)	(0.124)
Reg. Car	0.985	0.940	0.909′	0.869*	0.954	1.004	0.906	0.928	0.957	0.990
	(0.044)	(0.043)	(0.038)	(0.036)	(0.034)	(0.047)	(0.057)	(0.056)	(0.046)	(0.051)
PT Access	1.042	1.050	1.031	1.012	1.049°	1.088′	1.070	1.074	1.017	1.103′
	(0.035)	(0.039)	(0.032)	(0.033)	(0.029)	(0.042)	(0.054)	(0.049)	(0.041)	(0.045)
Egoistic	1.106*	1.085′	1.029	1.031	1.029	1.053	1.119′	1.028	1.056	1.008
	(0.039)	(0.040)	(0.033)	(0.031)	(0.028)	(0.041)	(0.053)	(0.047)	(0.042)	(0.042)
Biospheric	0.990	1.057	1.039	1.018	1.084*	1.039	1.013	1.060	1.056	1.058
	(0.034)	(0.039)	(0.035)	(0.035)	(0.033)	(0.042)	(0.051)	(0.051)	(0.044)	(0.047)
Traditional worker	1.145	1.061	1.006	0.823	1.047	1.949*	1.894*	1.079	1.412′	0.960
	(0.157)	(0.184)	(0.145)	(0.122)	(0.177)	(0.387)	(0.292)	(0.268)	(0.246)	(0.196)
Home-centered	0.935	0.960	0.987	0.968	1.004	0.950	1.099	1.024	1.025	1.054
	(0.079)	(0.077)	(0.080)	(0.070)	(0.072)	(0.079)	(0.112)	(0.102)	(0.095)	(0.109)
Entertainment-oriented	1.001	0.987	0.900	0.957	0.959	0.988	1.032	1.043	1.022	1.072
	(0.091)	(0.097)	(0.086)	(0.085)	(0.080)	(0.111)	(0.130)	(0.126)	(0.139)	(0.151)
Conventionalists	0.870	0.889	0.918	0.891	1.073	1.065	1.303′	1.135	1.024	1.061
	(0.098)	(0.092)	(0.083)	(0.085)	(0.076)	(0.119)	(0.155)	(0.135)	(0.127)	(0.111)
Advancement-oriented	1.059	1.004	1.065	1.001	1.015	1.079	1.139°	1.083	1.028	1.025
	(0.060)	(0.060)	(0.054)	(0.051)	(0.050)	(0.066)	(0.088)	(0.084)	(0.072)	(0.073)
Hedonists	0.990	1.005	0.989	1.061	1.038	1.041	1.103	1.086	1.003	1.044
	(0.062)	(0.065)	(0.056)	(0.061)	(0.056)	(0.081)	(0.107)	(0.092)	(0.077)	(0.082)
Conservatives	1.048	1.110	1.004	1.068	0.887°	0.913	1.140	0.998	0.861	0.924
	(0.154)	(0.143)	(0.107)	(0.080)	(0.059)	(0.114)	(0.124)	(0.103)	(0.079)	(0.078)
Liberals	0.931	0.906	0.934	0.960	0.950	1.006	1.060	1.009	0.991	1.004
	(0.057)	(0.058)	(0.051)	(0.049)	(0.044)	(0.063)	(0.085)	(0.076)	(0.072)	(0.074)
Pseudo-R^2	0.211									
N	352,140									
Participants	1,568									

Notes: *: $p < 0.01$, ’: $p < 0.05$, °: $p < 0.1$. Standard errors are clustered at the person-day level. This is the result from the final estimation of (4), after removing coefficients that did not meet a joint significance threshold (by variable group) of $p < 0.2$. The table shows the coefficients of the socio-demographic variable (rows) multiplied with the corresponding CP dummy (columns). The reference categories (in order) are: female, German-speakers, secondary education, household with 3 members, not working full time, not owning a car, using the car on <3 days per week, living in a zip code that does not have “high PT access” as defined by an index, not holding a PT subscription, belonging to the lifestyle category “reflexives”, and having a below-median index for “egoistic” and “biospheric” values. The model was estimated using PPML and person and day FE were absorbed. Standard errors are clustered on the participant level.

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